The Parametric Sensitivity of CAM5's MJO

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20   **Running Title:** Parametric Sensitivity of CAM5's MJO

21   **Key Points**

22   • Parameter values that improve CAM5's Madden-Julian Oscillation are identified
23   • Both microphysical and macrophysical deep convection parameters are important
24   • Simultaneously simulating the MJO and mean climate is challenging

Abstract

We systematically explore the ability of the Community Atmospheric Model Version 5 (CAM5) to simulate the Madden-Julian Oscillation (MJO), through an analysis of MJO metrics calculated from an 1100-member perturbed parameter ensemble of 5-year simulations with observed sea-surface temperatures. Parameters from the deep convection scheme make the greatest contribution to variance in MJO simulation quality with a much smaller contribution from parameters in the large-scale cloud, shallow convection and boundary layer turbulence schemes. Improved MJO variability results from a larger lateral entrainment rate and a shorter convective adjustment timescale. Improved variability also results from reductions to the drying tendencies of deep convection that were achieved by a smaller auto-conversion of cloud to rain water and a larger evaporation of convective precipitation. Unfortunately, simulations with an improved MJO also have a significant negative impact on the climatological values of low-level cloud and absorbed shortwave radiation, suggesting that structural in addition to parametric modifications to CAM5's parameterization suite are needed in order to simultaneously well simulate the MJO and mean-state climate.

1.   Introduction

41

42   Since its discovery and initial description by *Madden and Julian* [1971], the

43   Madden-Julian Oscillation (MJO) has been shown to be a dominant mode of Tropical

44   intra-seasonal variability with worldwide impacts [*Zhang,* 2005; *Lau and Waliser,* 2012].

45   The MJO is characterized by an eastward-propagating, equatorially-trapped baroclinic

46   oscillation in the tropical wind field and is associated with precipitation anomalies that

47   propagate from the western Indian Ocean to the western Pacific ocean with a

48   characteristic oscillation period of 40-50 days. Unlike other types of large-scale

49   equatorial wave modes, the existence of the MJO is not predicted by simple shallow

50   water theory [*Wheeler and Kiladis,* 1999]. Perhaps as a result, there has not yet been

51   established a comprehensive theory for the interactions of convective systems and large-

52   scale dynamics that create the MJO. Consequently, improved MJO understanding relies

53   on empirical studies utilizing satellite and field-campaign observations and models

54   ranging from general circulation models (GCMs) to cloud resolving models [*Zhang et al.,*

55   2013].

56   Despite the lack of a comprehensive theory, there is a significant understanding of

57   the necessary ingredients for the MJO. Most prominent are the role of moisture anomalies

58   and the sensitivity of convection to tropospheric moisture [*Bladé and Hartmann,* 1993;

59   *Sperber*, 2003; *Benedict and Randall*, 2007; *Maloney*, 2009; *Del Genio*, 2011; *Del Genio*

60   *et al.*, 2012; *Randall,* 2013; *Sobel and Maloney,* 2013]. During the suppressed phase of

61   the MJO (to the east of the convective center), convection depth is limited by a dry free

62   troposphere, but shallow cumuli moisten the atmosphere at the level at which they

63   detrain. This moistening potentially allows later convective events to rise through a more

64   humid atmosphere and thus penetrate somewhat higher, further recharging tropospheric

65   moisture, until the column is sufficiently humid to trigger the deep convection that

66   characterizes the disturbed MJO phase. The deep convection organizes and discharges the

67   built-up moisture through precipitation and compensating subsidence drying, returning

68   the atmosphere to the suppressed MJO phase. A complementary understanding involves

69   the variations of the diabatic heating with MJO phase [*Lin et al.,* 2004; *Zhang and Mu,*

70   2005; *Fu and Wang,* 2009; *Seo and Wang,* 2010; *Zhang et al.*, 2010; *Khouider et al.,*

71   2011; *Lappen and Schumacher,* 2012]. Previous authors have variously emphasized the

72   role of low-level heating in the build-up phase or the high-level heating associated with

73   stratiform precipitation during the active phase of convection, or its combined effect of a

74   east-to-west tilt in the level of maximum diabatic heating.

75   Of key interest in this study is the representation of the MJO in GCMs. While an

76   unconventional GCM in which the conventional convective parameterization has been

77   replaced by a two dimensional cloud resolving model can convincingly simulate the

78   space-time structure of the MJO [*Thayer-Calder and Randall,* 2009; *Stan et al.*, 2010],

79   the typical conventional GCM simulates an MJO that is too weak, if present at all [*Slingo*

80   *et al.,* 1996; *Lin et al.,* 2006; *Kim et al.,* 2009; *Jiang et al.,* 2014]. However, even with

81   conventional GCMs, there have been some encouraging results in individual models. In

82   particular, improved simulation results from inhibiting the deep convection either with

83   more restrictive closure assumptions [*Sperber et al.*, 2005; *Zhang and Mu,* 2005; *Lin et*

84   *al.,* 2008; *Benedict et al.*, 2013] or by increasing the lateral entrainment in convective

85   updrafts which enhances the sensitivity of the convection scheme to free tropospheric

86   moisture [*Tokioka et al.,* 1988; *Bechtold et al.,* 2008; *Del Genio et al.,* 2012; *Kim et al.,*

87   2011; *Zhou et al.,* 2012; *Hirons et al.*, 2012]. Given moisture's central role, it is not

88   surprising that some improvements can also be found by altering the moistening

89   tendencies of convection, for example by increasing the amount of evaporation of

90   convective rain [*Maloney,* 2009; *Del Genio et al.,* 2012]. While model resolution does

91   not consistently impact a simulated MJO [*Crueger et al.,* 2012; *Holloway et al.,* 2013], an

92   interactive ocean usually improves the MJO simulation [*Waliser et al.*, 1999; *Sperber et*

93   *al.*, 2005; *Woolnough et al.*, 2007; *Jiang et al.,* 2014]. However, the lack of an interactive

94   ocean is not viewed as the primary cause of poor simulations in atmosphere-only models,

95   as many coupled ocean-atmosphere models have a poor MJO [*Lin et al.*, 2006].

96   In this study, we examine the parametric sensitivity of the MJO simulation by the

97   Community Atmosphere Model Version 5 (CAM5) [*Neale et al.*, 2011]. While this

98   version of the model includes an entraining plume in its deep convection scheme [*Neale*

99   *et al.,* 2008] that improved the MJO in Version 4 of the coupled-ocean atmosphere model

100   [*Subramanian et al.*, 2011*, Zhou et al.,* 2012], the MJO is poorly simulated in

101   atmosphere-only versions of CAM4 [*Lappen and Schumacher*, 2012] and CAM5 [see

102   figures below and *Jiang et al.,* 2014]. Given the poor simulation of the MJO by CAM5

103   and the history of sometimes successful tinkering with the CAM parameterizations, the

104   question arises: Are there any choices of parameterization settings that could enable a

105   good simulation of the MJO? If so, would the improved simulation be consistent with

106   current understanding of the physical processes underlying the MJO?

107   To that end, we examine the MJO characteristics in a large ensemble of perturbed

108   parameter simulations of CAM5. Because the ensemble perturbs 22 uncertain parameters

109   across all major moist physical parameterizations, it gives one the opportunity to more

110   fully explore the multi-dimensional parameter space, thus addressing the problem that

111   most model developers perform sensitivity tests in an ad-hoc one-at-a-time manner. In

112   the case of CAM5, perturbed parameter ensembles have been previously used to study

113   the sensitivity of several precipitation characteristics including the mean and

114   convective/stratiform ratio [*Yang et al.*, 2013] as well as the diurnal cycle and

115   precipitation intensity distribution [*Qian et al.*, 2014]. These studies demonstrate that in

116   some cases, altering parameter values can improve model simulations in a significant

117   way; whether or not this is true for the simulated MJO is the focus of this paper.

118   The structure of the paper is as follows: Section 2 describes the model, perturbed-

119   parameter-ensemble, and observations used. Section 3 describes the metrics that quantify

120   MJO simulation quality, applies them to the ensemble, and presents an analysis of their

121   parametric sensitivity. In Section 4, another model simulation is described and additional

122   model diagnostics performed to test whether the suggestions from the sensitivity analysis

123   actually do improve the simulated MJO. Also presented in this section is a description of

124   changes to the mean-state climate that result from this attempt to improve the MJO. The

125   paper ends in Section 5 with a discussion of the major conclusions.

2.   The model, ensemble, and observations used

2.1.   CAM5

128   The GCM used here is the Community Atmosphere Model Version 5 (CAM5)

129   [*Neale et al.*, 2011], specifically version cam5_1_02. All simulations use the finite

130   volume dynamical core with a horizontal resolution of 1.9° x 2.5° latitude by longitude

131   and 30 vertical levels. Table 1 contains the descriptions of the parameterizations used in

132 CAM5. Of note is that the deep convection parameterization is based upon Zhang-

133 McFarlane [*Zhang and McFarlane*, 1995], but modified to include an entraining plume

134 and cumulus momentum transport [*Neale et al.*, 2008].

2.2. Perturbed parameter ensemble

136   The CAM5 perturbed-parameter ensemble used here was performed for another

137 project and is fully described elsewhere (see specifically the C-Ensemble in *Qian et al.*

138 [2014]). In brief, all members of the ensemble were CAM5 integrations of 5 years length

139 using monthly mean observed sea-surface temperatures from 2000 to 2004. The ensemble

140 consists of 1100 members (actually five separate ensembles of 220 simulations each) that

141 were generated with Latin Hyper-Cube sampling for the values of 22 parameters that

142 span CAM5's convection (shallow and deep), cloud, and turbulence parameterizations.

143 All parameters are varied simultaneously with each parameter having a uniform

144 distribution of values over all ensemble members. Table 2 shows the default value and

145 ranges of the parameters varied. Parameter uncertainty ranges were determined by expert

146 solicitation based upon physical considerations. Selected parameters of the deep

147 convection scheme are described in more detail in Appendix A; the rest of the parameters

148 have extended descriptions in the CAM5 scientific description [*Neale et al.* 2011].

2.3. Observations and analysis data

150   The following precipitation datasets are used to characterize the observed MJO:

151 the Global Precipitation Climatology Project (GPCP) [*Adler et al.*, 2003], the Tropical

152 Rainfall Measuring Mission (TRMM) [*Huffman et al.*, 2007], and (as a precipitation

153 surrogate) outgoing longwave radiation (OLR) estimates from *Liebmann and Smith*

154 [1996]. Daily estimates for these products are available for the years 1996 to 2009 for

155 GPCP, 2000 to 2009 for TRMM, and 1980 to 2011 for the OLR estimate. For large-scale

156 winds associated with the MJO, we use re-analysis data for the years 1980 to 2011 from

157 the European Centre for Medium-Range Weather Forecasts (ERA-Interim) [*Dee et al.*

158 2011].

159   For characterization of model climate, we additionally use satellite estimates of

160 radiation from the Clouds and Earth's Radiation Energy Systems (CERES) Energy

161 Balanced And Filled (EBAF) dataset [*Loeb et al.*, 2009] and oceanic cloud liquid water

162 path from the National Aeronautics and Space Administration Water Vapor Project

163 (NVAP) [*Randel et al.*, 1996].

164   **3.**   **An analysis of the MJO sensitivity in the ensemble**

165   **3.1.**   **Metrics for the MJO and their variability in the ensemble**

166   The comprehensive diagnostics described in *CLIVAR* [2009] were reviewed to

167 determine appropriate measures to characterize the MJO in the perturbed parameter

168 ensemble, subject to the constraint that precipitation was the only sub-monthly output

169 available. Three diagnostics that appear to be powerful at discriminating the MJO were

170 selected and for each the information was further reduced into a single number or

171 'metric'. The analysis was restricted to the boreal winter months of November to April,

172 the months with the most pronounced MJO activity.

173   The first two metrics can best be described by reference to Figure 1, which shows

174 time lag – longitude plots of correlation coefficients between 10°S - 10°N averaged intra-

175 seasonal TRMM precipitation anomalies with intra-seasonal precipitation for a base

176 region in the Indian Ocean region (Figure 1a, 70°E -90°E, 5°S - 5°N) and the Western

177 Pacific Ocean (Figure 1b, 130°E - 150°E, 5°S to 5°N). Intra-seasonal precipitation was

178 calculated with a band-pass filter of 20 to 90 days. These plots show the progression of

179 MJO precipitation eastward from the Indian Ocean into the West Pacific Ocean.

180 Corresponding figures were constructed for each ensemble member and the first metric

181 (called *patCorACIO*) was set equal to the pattern correlation coefficient over the plotted

182 domain (30°E - 180°E, -20 - +20 days) between the model result and the observed using

183 the Indian Ocean base region (Figure 1a). The second metric (called *patCorACWP*) was

184 created in an identical fashion but with using the Western Pacific Ocean base region. For

185 both metrics, a perfect model result would be indicated by a metric with value of +1.0

186 (perfect correlation).

187   The third metric is described by reference to Figure 2 which displays the

188 November to April wavenumber frequency spectra of 10°S - 10°N averaged TRMM

189 precipitation. The computation was carried out as described by *CLIVAR* [2009]. The

190 actual metric (called *wePwrRatio*) is the ratio of power in Eastward to Westward

191 propagating waves. The power is calculated for frequencies with periods between 20 and

192 90 days and zonal wavenumbers 1 to 5. In Figure 2, this ratio is computed from the

193 average power over the two outlined boxes. For TRMM, *wePwrRatio* has a value of 2.18.

194   These metrics are complementary since *patCorACIO* and *patCorACWP* capture

195 the MJO phase speed and geographical characteristics whereas *wePwrRatio* provides a

196 measure of MJO magnitude and scale.

197   Figure 3 displays the joint histogram of *patCorACIO* and *wePwrRatio* calculated

198 from all 1100 members of the ensemble as well as from a separate integration of CAM5

199   when run with the default parameter settings. Figure 3a displays the results of metrics

200   calculated using the GPCP precipitation estimate and Figure 3b presents the results using

201   TRMM precipitation. Although the exact values of *wePwrRatio* and *patCorACIO* do

202   vary with the choice of precipitation datasets, the general impression remains the same.

203   Namely, the default model and the majority of models in the ensemble do not perform

204   particularly well using these metrics, with a relatively low pattern correlation (typically

205   less than 0.5) and no preference for eastward propagating low-frequency waves unlike

206   the observations. Despite this, there are a few dozen or so ensemble members that do

207   perform relatively well with pattern correlations in excess of 0.7 and East-West power

208   ratios approaching 2. Results using *patCorACWP* instead *patCorACIO* are similar.

209   **3.2.   The parametric sensitivity of the MJO metrics and a Bayesian parameter**

210   **estimation**

211   Given the wide range of model performance across the ensemble, it may be

212   possible to identify which parameters influence the simulated metrics and which

213   parameters are immaterial to the simulation of the MJO. A further goal would be to

214   estimate the optimal value for each parameter given the observed value of the metrics.

215   These goals are accomplished using statistical techniques described in Appendix B that

216   specialize in the analysis of variance and parameter estimation.

217   Figure 4 summarizes the relative importance of the perturbed parameters in

218   explaining variance in the simulated *patCorACIO, patCorACWP* and *wePwrRatio*.

219   Larger values of feature scores, roughly analogous to the fraction of variance explained,

220   indicate greater impact of a parameter. For all metrics, parameters from the deep

221   convection scheme dominate the ensemble variance with perhaps surprising little

222   influence from parameters from other parameterization schemes. The most important

223   parameters are the timescale for deep convection (*zmconv_tau*) and the mass entrainment

224   rate (*zmconv_dmpdz*), with the parameters controlling precipitation and evaporation

225   efficiency (*zmconv_c0_ocn* and *zmconv_ke*, respectively) and the magnitude of the

226   downdraft mass-flux (*zmconv_alfa*) also being important, particularly for *patCorACIO*

227   and *patCorACWP*.

228   Recommended values for these parameters can be discerned from Figure 5 which

229   shows the marginal parameter posterior distributions for *zmconv_tau*, *zmconv_dmpdz*,

230   *zmconv_c0_ocn*, *zmconv_ke* and *zmconv_alfa* over their normalized range from 0

231   (minimum value) to 1 (maximum value). The red vertical lines indicate the normalized

232   values that correspond to CAM5's default parameter settings. Larger values indicate

233   increased likelihood of that parameter value leading to a simulation that would improve

234   the agreement of with the observed values of *patCorACIO*, *patCorACWP* and

235   *wePwrRatio*. The figure suggests than an improved simulation would result from setting

236   *zmconv_c0_ocn*, *zmconv_tau* and *zmconv_alfa* to their minimum values and

237   *zmconv_dmpdz* and *zmconv_ke* to their maximum values. Because the most likely

238   parameter values fall at the boundaries of the parameter sampling ranges, it suggests that

239   true optimum values of these parameters may lie outside the sampled ranges of the

240   parameters. Because the parameter ranges are set by expert judgment regarding their

241   physical plausibility, an optimal value outside the specified ranges may indicate structural

242   deficiencies in the physical parameterizations of the climate model [*Neelin et al.*, 2010].

243 **4.** **Can the MJO be improved, and if so, what are the**

244 **consequences for the mean climate?**

245 **4.1. The MJO of a targeted simulation**

246   The sensitivity analysis presented in the previous section provides guidance as to

247 which parameters the simulated MJO metrics are sensitive to and recommends suggested

248 values. However, because no single run in the ensemble changed all of the parameters in

249 the recommend way and all runs contain changes to other parameters that were at best

250 insignificant to the MJO, it remains to be demonstrated that this guidance would actually

251 improve the simulated MJO. Furthermore, model optimization of these three metrics may

252 not produce a realistic MJO when one considers MJO characteristics other than those

253 measured by the metrics.

254   Thus, a targeted new simulation (called *UQ-Rec*) was performed in which the

255 only parameters changed were those in the deep convection parameterization suggested

256 by the sensitivity analysis to have an influence on the simulated MJO (see Appendix A

257 for their description). Specifically, the rate at which liquid is converted into rain inside

258 the updraft over ocean (*zmconv_c0_ocn*) is set to the lower limit from Table 2, a

259 reduction by a factor of 45 with respect to the default. Second, the evaporation of

260 convective precipitation was increased by raising the efficiency parameter (*zmconv_ke*)

261 by a factor of 10, setting its value equal to the upper limit from Table 2. Both changes

262 reduce the drying tendencies of deep convection, effectively lowering its precipitation

263 efficiency. Third, the convective time scale (*zmconv_tau*) was set to its lower limit from

264 Table 2, effectively doubling the cumulus mass-flux for a given large-scale condition. No

265   changes were made to the other two parameters (*zmconv_dmpdz* and *zmconv_alfa*), since

266   Figure 5 suggests that little additional gain would result, given that the likelihood of the

267   default setting is nearly as large as the maximum likelihood in the tested range.

268   In order to increase the statistical robustness, a ten-year simulation for *UQ-Rec*

269   covering the years 2000-2009 was performed. As a point of comparison, two additional

270   ten-year simulations were also performed for the model with the default parameter

271   settings (called *Default*) and the single member of the perturbed parameter ensemble that

272   scored best in terms of the MJO metrics (called *PPE-Best*). While all 22 parameters in

273   *PPE-Best* differ in their settings from their defaults, *PPE-Best* shares similarities to *UQ-*

274   *Rec* including a factor of 15 reduction in *zmconv_c0_ocn* relative to the default CAM5, a

275   halving of *zmconv_tau*, and a factor of 2.5 increase in *zmconv_ke*.

276   The analysis of the simulated MJO in these runs begins with an examination of

277   the diagnostics upon which the MJO metrics are based. Figure 6 shows the lag-longitude

278   plots of boreal winter intra-seasonal precipitation anomalies (color shading) for the

279   TRMM observations and the three model runs correlated with Indian ocean intra-seasonal

280   precipitation. Overlain on these plots are the correlation coefficients for the 850 hPa

281   zonal wind anomalies with Indian ocean intra-seasonal precipitation. The *UQ-Rec*

282   appears to have better eastward propagation for both the OLR and 850 hPa wind

283   anomalies, especially over the Indian Ocean and west Pacific. In the other two

284   simulations, the OLR tends to show more of a standing oscillation over the Indian Ocean,

285   with pronounced westward propagation of 850 hPa wind anomalies.

286   The improved eastward propagation in the UQ-Rec simulation is also confirmed

287   in Figure 7, which displays the wavenumber − frequency spectra of tropical precipitation

288   from the model simulations calculated in the same way as that of the observations shown

289   in Figure 2. Here there are striking differences in magnitude of intra-seasonal variance

290   (consider the different color scales) with the *PPE-Best* and particularly *UQ-Rec*

291   simulations having considerably larger amounts of intra-seasonal variance relative to that

292   in the *Default* simulation. The increased variances are accompanied by significant

293   increases in the ratio of Eastward to Westward propagating waves with the value of the

294   *wePwrRatio* in the *UQ-Rec* simulation (2.01) lying within the range of the observed

295   estimates. However, accompanying these improvements are some persistent deficiencies

296   including a tendency for the maximum power to occur at too low a frequency (in both

297   eastward and westward propagating variance) and for variance to peak at wave number

298   two without extending to wave number one as in observations. These behaviors have also

299   been found in other models [*Kim et al.* 2009].

300   Extending the analysis to other MJO diagnostics (often following *CLIVAR*

301   [2009]), Figure 8 shows the first multivariate combined Empirical Orthogonal Function

302   (CEOF) of the 20 – 90 day band-passed OLR, 850 and 200 hPa zonal winds averaged

303   from 15°S to 15°N for the boreal cool season for the observations and models calculated

304   as in *Wheeler and Hendon* [2004]. While all simulations exhibit the out-of-phase

305   relationship between 850 hPa and 200 hPa zonal winds as seen in the observations, they

306   all struggle to exhibit the observed quadrature relationship for OLR with winds in the

307   Indian ocean. In terms of the fraction of variance explained, the *UQ-Rec* simulation has

308   the highest fraction of variance explained (18.8%) which while still less than observed

309   (22.9%) is noticeably higher than that of the *Default* (14.9%). Results are similar for the

310   second CEOF (not shown), which explains a similar amount of variance as CEOF 1 (in

311   both the models and observations). Here too, the relative superiority of the *UQ-Rec*

312   simulation is illustrated by the values of the correlation coefficient and lag time with the

313   maximum correlation between the principal component (PC) time-series corresponding to

314   CEOF 1 and CEOF 2. In particular, the values from the *UQ-Rec* simulation (0.76 and 9

315   days) are closer to the observed values (0.78 and 10 days) than are the values from the

316   *Default* simulation (0.61 and 9 days). This indicates an improved temporal coherency for

317   the eastward propagating signal.

318   MJO amplitude can also be gauged from Figure 9, which shows power-spectral

319   density plots of the CEOF 1 (Figure 8) projected onto the unfiltered data (with only the

320   seasonal cycle removed). Of all the simulations, the *UQ-Rec* has by far the largest

321   amplitude across all frequencies although it must be noted its amplitude is still less than

322   observed. Furthermore, all simulations have too much amplitude in the lowest frequency

323   near 100 days with the frequency of the peak power shifted by 20 - 30 days from the

324   observations.

325   For a qualitative overview of the structure of the MJO simulations, Figure 10 is a

326   composite of November to April band-passed OLR as a function of MJO phase for the

327   observations and the three simulations. The composites are based on $PC1^2 + PC2^2 > 1$ in

328   each octant of the PC1 vs. PC2 phase space, where PC1 and PC2 are the unit standard

329   deviation principal components corresponding to CEOF 1 and CEOF 2. The *Default*

330   simulation has an almost no evidence of a definitive MJO structure. In contrast, the *UQ-*

331   *Rec* simulation has a fairly good correspondence with observations with its weakest point

332   being in phase 5 when it substantially underestimates the signal over the Maritime

333   Continent. Curiously, the *PPE-Best* simulation has poor features at the initial and final

334   phases but does rather well at phase 5. The improved result over the land of the maritime

335   continent in the *PPE-Best* simulation may be because *zmconv_c0_land* is a factor of 4

336   less than in the *Default* and *UQ-Rec* simulations.

337   Figure 11 is a similar composite but for the 850 hPa zonal wind. While the

338   general character of the *Default* simulation appears reasonable, its amplitude is smaller

339   than the observations. In contrast, the amplitudes of the fluctuations are larger (and

340   perhaps a bit too large relative to observations) for the *PPE-Best* and *UQ-Rec*

341   simulations. The generally better performance of the simulations for the 850 hPa zonal

342   wind relative to OLR is symptomatic of the fact that the large-scale dynamics is easier to

343   simulate relative to that of the precipitation [*Crueger et al.*, 2012].

344   From the literature cited in the introduction, one would expect that the eastward

345   moving convection center would be proceeded by low-level moistening and heating with

346   upper level moistening and mid to lower level clearing in its wake. Figure 12 presents

347   longitude-pressure cross-sections of specific humidity anomalies from 15°S to 15°N

348   linearly regressed onto the 20 − 90 day band-passed precipitation at 120°E. The re-

349   analysis shows significant low-level positive anomalies to the east of 120°E with mid-

350   level drying to the west. The *UQ-Rec* simulation has a pattern in many respects similar to

351   the re-analysis including positive moisture anomalies beneath 900 hPa to the east of

352   120°E, and negative moisture anomalies to the west. The other model simulations fail to

353   show the positive low-level moisture anomalies to the east.

354   Figure 13 is the same as Figure 12 except for displaying the anomalies in moist

355   diabatic heating (convective plus stratiform). The estimate from the ERA-Interim for this

356   can be found in Figure 10a of *Benedict et al.* [2013]. Of the three model simulations, the

357   *UQ-Rec* simulation has the most pronounced low-level heating to the east of 120°E and is

358   most close to the re-analysis.

359   **4.2 What are the consequences for the mean model climate state?**

360   Figures 6 to 13 indicate that modifying a few parameters of the deep convection

361   scheme as done in the *UQ-Rec* model configuration improves the simulated MJO.

362   However, these parameter settings may not be acceptable for the model if the simulation

363   of the mean climate were seriously degraded. In terms of mean precipitation, the *UQ-Rec*

364   simulation performs nearly as well as the *Default* with a 40% smaller bias and 2.5%

365   increase in root-mean-square error (Table 3). Relative to the *Default*, the *UQ-Rec*

366   simulation has increased precipitation on the equator in the Western Pacific and in the

367   South Pacific Convergence Zone with reduced precipitation in the Northern Hemisphere

368   Tropics which is an improvement (not shown). In the *UQ-Rec* simulation, the fraction of

369   precipitation produced from the stratiform or large-scale cloud parameterization increases

370   to 11% from 6% in the *Default* simulation. This is less than the 30% stratiform

371   precipitation fraction that was thought to be important for the MJO simulation of two

372   other models [*Fu and Wang*, 2009; *Seo and Wang*, 2010].

373   However, in terms of the climatological radiation field, a very strong bias in

374   excess of 20 W m^{-2} has been introduced into the global mean shortwave radiation cloud

375   radiative effect through the modification of perturbed parameters in both the *UQ-Rec* and

376   *PPE-Best* simulations (Table 3). A bias of this magnitude is unacceptable for a climate

377   model. This increase in reflected shortwave radiation is due to a very large increase in

378   column integrated liquid water path (LWP), with values in the *UQ-Rec* and *PPE-Best*

379   simulations that are 4 times that observed. A single perturbation experiment (called

380 *OAT38*) changing only *zmconv_c0_ocn* suggests that the decrease in this parameter is

381 responsible for most of this increase in LWP and reflected shortwave radiation.

382 Physically, by lowering the rate at which convective cloud condensate is converted to

383 precipitation, more convective condensate is left as cloud water that can reflect shortwave

384 radiation. A related consequence is an increase in lower tropospheric moisture (Figure

385 14). Compared to the *Default* simulation and the re-analysis, all modified simulations

386 exhibit a considerably moister lower troposphere with typical increases of 2 g kg^{-1}

387 particularly in the layer between 500 and 800 hPa. These are the same levels that

388 contribute to the very strong increase in LWP.

389   It is clear if one were to use the guidance from this study to improve CAM5's

390 MJO, one would need to eliminate these biases in clouds and reflected shortwave

391 radiation. Given that a bias of this magnitude is likely outside of the range that could be

392 eliminated with further parameter modifications (i.e. routine model tuning), structural

393 modifications to CAM5's parameterization suite would be needed.

394 5. Discussion

395   The motivating question for this study was: *Are there any choices of CAM5's*

396 *parameterization settings that could enable a good simulation of the MJO?* The answer

397 seems to be a qualified yes. By modifying 5 key parameters in the deep convection

398 parameterization based upon guidance from a very large perturbed-parameter ensemble,

399 the simulation of the MJO is improved, particularly in terms of the amplitude of the intra-

400 seasonal variability and the simulation of low-level moisture and heating anomalies to the

401 east of the convective center. However, the improved MJO still has noticeable

402 deficiencies, particularly with an oscillation period that is too long. This would seem to

403   be a qualified success for the perturbed-parameter methodology; namely, metrics for the

404   MJO were defined *a priori*, a sensitivity analysis then found the parameters that influence

405   the metrics, and *a posteori* simulation demonstrated that guidance from the sensitivity

406   analysis was correct. Note that partial success was not guaranteed from the start; two

407   other possibilities were that no perturbations to the parameters chosen would have

408   successfully improved the MJO, or that the analysis techniques could have missed

409   possible ways to improve the MJO. However, given the systematic nature of the UQ

410   exploration, we are confident that we have found the only ways to improve the MJO in

411   CAM5 based on modification to the 22 parameters considered.

412   The major drawback of this approach is that fixing one aspect of the simulation

413   may introduce problems into other aspects of the model's simulation. While the

414   simulation of climatological precipitation is acceptable, the mean amount of absorbed

415   shortwave radiation is unacceptably reduced, primarily as a result of the one parameter

416   (*zmconv_c0_ocn*) that is most effective at improving the MJO. It should also be noted

417   that the tunings suggested here are in apparent disagreement with those suggested from

418   other perturbed-parameter studies with CAM5 to improve other aspects of the simulated

419   precipitation field. In particular, to improve the ratio of stratiform to convective scale

420   precipitation, *Yang et al.* [2013] suggest that lengthening the convective adjustment time

421   scale (*zmconv_tau*) and increasing the initial downdraft mass-flux (*zmconv_alfa*) relative

422   to CAM5's default settings; guidance which is opposite to that found here for improving

423   the MJO. *Qian et al.* [2014] also suggest that the adjustment time scale (*zmconv_tau*)

424   should be lengthened to increase the value of the 95th percentile of hourly mean

425   precipitation distribution.

426　　　　　In terms of the physics of convection and its relationship to the MJO, the present

427　　study confirms the now well-known sensitivity of tropical variability to the lateral

428　　entrainment rate of the deep convection scheme. The present study also confirms the

429　　previously known importance of processes that affect the ultimate drying tendencies of

430　　the deep convection parameterization, including both the rate at which convective

431　　precipitation evaporates and the representation of cloud microphysics in the

432　　parameterized convective updrafts. But there are differences too with prior work. In

433　　particular, the simulation of the MJO is improved by shortening the adjustment time scale

434　　for deep convection for which we do not have a physical explanation. Also somewhat

435　　surprising is the relative insensitivity to parameters from processes other than the deep

436　　convection scheme. If the buildup of moisture in advance of the MJO deep convective

437　　phase is so important, why weren't the simulations of the MJO sensitive to the mixing

438　　(*uwshcu_rkm* and *uwshcu_rpen*) or microphysical (*uwshcu_criqc* and *uwshcu_kevp*)

439　　parameters in the shallow convection scheme [*Cai et al.*, 2014]? Likewise, if the radiative

440　　heating associated with clouds is an important amplifier on the variability of tropical

441　　convection, why weren't the simulations of the MJO sensitive to changes in the key ice

442　　microphysical parameters (*cldwatmi_dcs*, *cldwatmi_ai*, and *cldwatmi_as*) that affect the

443　　amount of ice in high-level stratiform anvils associated with convection? Two possible

444　　answers to these questions are (a) that these parameters were not perturbed over a wide

445　　enough range to simulate a noticeable effect or (b) it may be that shallow convection and

446　　radiative heating (at least in CAM5, if not nature) are not that important to the MJO. A

447　　further caution on the guidance from perturbed parameter ensembles is that the

448   recommend parameter values may improve the simulation of the phenomenon for the

449   wrong physical reason [*Hannah and Maloney*, 2014].

450   Clearly discretion should be exercised as to how and when it is suitable to use

451   parameter perturbations to improve the simulation of selected phenomena. Perhaps the

452   knowledge gained in this paper might be useable in a qualitative way in future tuning

453   exercises with CAM when other significant model changes in either in resolution or

454   model physics have occurred. For example, knowledge of which parameters affect the

455   simulated MJO can be used when making choices in an ultimate tuning of a climate

456   model, when it is necessary to balance the simulation quality of a model across many

457   diverse metrics. The other way in which the knowledge gained in this study may be

458   useful is in the encouragement of the development of separate structural changes to

459   model physics. In light of the results presented here, parameterization developments for

460   the CAM aimed at increasing the sensitivity of the deep convection scheme through

461   treatments of mesoscale organization [*Mapes and Neale*, 2011; *Park*, 2014] and reducing

462   the drying tendencies of deep convection parameterizations through alterations to the

463   treatment of convective-scale microphysics [*Song et al.*, 2012] would seem promising as

464   means to improve the MJO.

465

Acknowledgments

Appendix A: Description of selected parameters in CAM5's Zhang-McFarlane cumulus parameterization

478

479

480   The production rate of rain water (R_r) from cloud liquid water in the Zhang-

481   McFarlane cumulus parameterization is given by:

$$R_r = C_0 M_u Q_l \tag{A1}$$

482

483   where M_u is the updraft mass flux, C_0 is the autoconversion coefficient, and Q_l is the

484   cloud liquid water content. Smaller values of C_0 decrease the rate of conversion of cloud

485   water to rain. In CAM5, C_0 is permitted to have different values over land and ocean and

486   corresponds to the entries *zmconv_c0_lnd* and *zmconv_c0_ocn* in Table 2.

487   The closure condition assumes that cumulus convection consumes Convective

488   Available Potential Energy (*CAPE*) at a certain rate F per unit updraft mass flux at cloud

489   base (M_b). Knowing F, M_b is calculated as:

$$M_b = \frac{CAPE - CAPE_0}{\tau F} \tag{A2}$$

490

491   where $CAPE_0$ is the threshold for deep convection and τ is a prescribed time scale

492   during which $CAPE$ in excess of $CAPE_0$ is consumed by convection. τ corresponds to

493   the entry *zmconv_tau* in Table 2.

494   The rate of evaporation of precipitation E_k directly into the grid scale

495   environment as it falls to the surface is given by:

$$E_k = K_e \left(1 - RH_k\right) R_k^{1/2} \tag{A3}$$

496

497   where R_k is the total rainwater flux in model layer k, RH is the relative humidity of the

498   environment, and K_e is the evaporation efficiency. K_e corresponds to the entry

499   *zmconv_ke* in Table 2.

500   In the original Zhang-McFarlane scheme, $CAPE$ is diagnosed by assuming an

501   undiluted parcel ascent. However, in CAM5, deep convection is assumed to take place

502   with an entraining air parcel that mixes with the free troposphere proportional to an

503   assumed constant entrainment rate [*Neale et al.*, 2008; *Zhou et al.* 2012]. The entrainment

504   rate corresponds to the entry *zmconv_dmpdz* in Table 2.

505   Downdrafts are assumed to start at the mid-tropospheric minimum in saturated

506   moist static energy and detrain in the sub-cloud layer. The downdraft mass flux is scaled

507   with the updraft mass-flux where the proportionality factor α is given by:

508
$$\alpha = \frac{\mu P}{P + E_d} \tag{A2}$$

509   where P is the total precipitation in the convective layer and E_d is the rain water

510   evaporation required to maintain the downdraft in a saturated state. This formalism

511   ensures that the downdraft mass flux vanishes in the absence of precipitation, and that

512   evaporation cannot exceed some fraction µ of the precipitation. µ corresponds to the entry

513   *zmconv_alfa* in Table 2.

514

515 **Appendix B: Sensitivity analysis and Bayesian parameter**

516 **estimation**

517   Two stages of analysis were performed on the *patCorACIO*, *patCorACWP* and

518 *wePwrRatio* metrics calculated from the perturbed-parameter ensemble. First, a

519 parameter sensitivity analysis was performed to identify the perturbed parameters (also

520 called input parameters here) that are most responsible for the variance in the MJO

521 metrics. Second, given observational targets for *patCorACIO*, *patCorACWP* and

522 *wePwrRatio*, a Bayesian parameter estimation was applied to determine posterior

523 distributions for those parameters identified in the first stage to be most responsible for

524 the variance in the metrics. Both stages utilized statistical response surface models that

525 relate the values of the CAM5 parameters to the MJO metrics. Before fitting these

526 response surface models, the *patCorACIO*, *patCorACWP* and *wePwrRatio* distributions

527 were centered to have a mean of 0 and unit standard deviation. For the parameter

528 sensitivity analysis, 80% of the data was randomly selected for fitting the response

529 surface models and the remaining 20% used for testing quality of the fits.

530   In the first stage, the sensitivity analysis was conducted using response surface

531 models for *patCorACIO*, *patCorACWP* and *wePwrRatio* as a function of the 22 input

532 parameters. Although other methods including linear basis functions, polynomial chaos

533 expansions [*Lucas et al.*, 2013], and support vector machines [*Bishop*, 2007] were tried,

534 random forests [*Breiman*, 2001] were selected as they yielded the best fits. Briefly, a

535 random forest is an ensemble of randomized decision trees. Individual trees in the forest

536 are generated by bootstrap sampling with replacement of the training data and selecting

537 random subsets of the input parameters for partitioning the input data space. A variant of

538 random forests, called extremely randomized trees [*Geurts et al.*, 2006], was used that

539 adds a further level of randomization to the partitioning. Random forests are

540 straightforward to fit and attractive because they make essentially no assumptions about

541 the relationships in the data. The extra trees implementation contained in the Scikit-learn

542 package [*Pedregosa et al.*, 2011] was used with all of its default settings except the

543 number of trees, which was set to 50. From the random forests, parameter sensitivities

544 with error estimates were derived in terms of feature scores that approximate the fraction

545 of ensemble variance explained by the parameter variations. Important parameters have

546 large feature scores and the error estimates are traceable to the variability in the ranks

547 across trees in the forest.

548   In the second stage, Bayesian parameter estimation was performed for the five

549 parameters with the largest feature scores. The goal is to determine the parameter values

550 that hypothetically would improve the agreement between the simulated and observed

551 values of *patCorACIO*, *patCorACWP* and *wePwrRatio*. Response surfaces are an

552 indispensable tool for this analysis because they are used to quickly estimate the values of

553 the metrics at new, untested values of the input parameters without the need to run

554 additional CAM5 simulations. To that end, the random forest response surfaces were refit

555 using only the selected parameters from all ensemble members. Subsequently, Bayes'

556 rule (posterior ∝ likelihood×prior) is applied with samples drawn from a prescribed

557 prior probability distribution over the parameters, and for each sample point the

558 likelihood of explaining the observations is calculated. The likelihood and prior

559 distributions are multiplied and normalized to yield a posterior probability distribution

560 over the parameters. Following the parameter sampling distribution, we use uniform prior

561   distribution over the ranges of the selected parameter ranges defined in Table 2, which

562   simplifies the Bayesian calculations (i.e. the likelihood is multiplied by 1). We draw 10^6

563   samples from this prior distribution using Latin Hypercube Sampling, and then evaluate

564   *patCorACIO*, the *patCorACWP* and *wePwrRatio* using the random forest response

565   surfaces. The logarithm of the likelihood is computed as $\log L = -\Big[\big(r_{patCorACIO} -$

566    $t_{patCorACIO}\big)^2 + \big(r_{patCorACWP} - t_{patCorACWP}\big)^2 + (r_{wePwrRatio} - t_{wePwrRatio})^2\Big]/2\delta^2,$

567   where r and t are, respectively, the centered response surface and target (i.e., observed)

568   values of *patCorACIO*, *patCorACWP* and *wePwrRatio*, and δ^2 approximates the variance

569   of the squared differences. The target values are taken as 1.0, 1.0 and 2.18 for

570   *patCorACIO*, *patCorACWP* and *wePwrRatio*, and δ is set as 2.5 standard deviations of

571   the centered distributions. Our focus is on identifying likelihood maxima (i.e. optimal

572   parameter values) rather than determining the precise shape of the likelihood distribution

573   (i.e. parameter uncertainties), so the actual value of the δ used is somewhat arbitrary.

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782   parameterizations, *Journal   of   Climate,   25(4),*   1116–1136,

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784

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786 FIGURE 1. Lag-longitude correlation coefficients of TRMM precipitation averaged from

787 10°S - 10°N with TRMM precipitation averaged over the (a) the Indian Ocean region

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795 correspond to periods between 20 and 90 days and for wavenumbers 1 – 5. Individual

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799 FIGURE 3. Joint histogram across the ensemble of East-West Power Ratio (*wePwrRatio*)

800 and lead-lag/longitude pattern correlation (*patCorACIO*) using (a) GPCP and (b) TRMM

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802 the color shading whose legend is shown to the right of the plot. The star indicates the

803 values of these metrics for the CAM5 with its default settings. The large black circle at

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809   metrics of *patCorACIO*, *patCorACWP*, and *wePwrRatio*.

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811   deep convection parameters using random forest evaluations and observations of

812   *patCorACIO*, *patCorACWP* and *wePwrRatio*. The abscissa displays the scaled parameter

813   values between 0 (minimum) and 1 (maximum), and the vertical red lines denote the

814   default parameter values used in CAM5. These plots can be used to indicate the relative

815   likelihood of a given parameter value. For example, CAM5 simulations in which

816   *zmconv_c0_ocn* is set to its minimum value are much more likely than any other value

817   including CAM5's default to lead to simulations which more closely match the observed

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827   of the *UQ-Rec* and *PPE-Best* simulations.

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831   are from ERA-Interim for winds and *Liebmann and Smith* [1996] for OLR.

832   FIGURE 9. Power-spectral density plots of the leading CEOF (FIGURE 8) projected

833   onto the unfiltered data with only the seasonal cycle removed for the (a) observations and

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841   are in m sec^{-1}.

842   FIGURE 12. Longitude-pressure cross-sections of 15°S to 15°N averaged specific

843   humidity anomalies linearly regressed onto 10°N - 10°S averaged 20 – 90 day band-

844   passed precipitation at 120°E for (a) ERA-Interim and the (b) *Default*, (c) *UQ-Rec*, and

845   (d) *PPE-Best* simulations. Positive values are indicated by solid contours whereas

846   negative values are indicated by dashed contours. Shading indicates where anomalies are

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848   FIGURE 13. As in FIGURE 12, but for diabatic heating.

849   FIGURE 14. Longitude-pressure cross-sections of water vapor specific humidity

850   differences in g kg^{-1} between the ERA-Interim re-analysis and the (a) *Default*, (b) *UQ-*

851   *Rec*, (c) *PPE-Best*, and (d) *OAT38* simulations. Differences are averaged over the months

852   of November through April and from 15°N-15°S with positive values indicating that the

853   simulated specific humidity is larger than that in the re-analysis.

854   TABLE 1. Summary of CAM5 parameterizations.

Parameterizations	CAM5 Implementation
Radiation	Rapid Radiative Transfer Model - Global [*Iacono et al.*, 2008]
Shallow convection	Mass flux scheme with convective inhibition closure [*Park and Bretherton*, 2009]
Deep convection	Bulk mass flux with CAPE closure and an entraining plume [*Zhang and McFarlane*, 1995; *Neale et al.*, 2008]
Planetary boundary layer and turbulence	Moist turbulence scheme based on di- agnostic turbulent kinetic energy [*Bretherton and Park*, 2009]
Cloud microphysics and macrophysics	Prognostic double moment microphysics, [*Morrison and Gettelman*, 2008; *Gettelman et al.*, 2010] and diagnostic cloud fraction scheme
Aerosols	Modal aerosol model [*Liu et al.,* 2012]

1 TABLE 2. Parameters varied in the perturbed parameter ensemble.
2

Model Variable	Variable Description	Parameterization	Minimum Value	Default Value	Maximum Value
dust_emis_fact	Dust emission tuning factor	Aerosol	0.21	0.35	0.86
cldfrc_rhminh	Threshold relative humidity for high-level clouds	Large-scale cloud	0.65	0.8	0.85
cldfrc_rhminl	Threshold relative humidity for low-level clouds	Large-scale cloud	0.8	0.8875	0.99
cldwatmi_ai	Fall speed parameter for stratiform cloud ice	Large-scale cloud	350	700	1400
cldwatmi_as	Fall speed parameter for stratiform snow	Large-scale cloud	5.86	11.72	23.44
cldwatmi_cdnl	Cloud droplet number limiter	Large-scale cloud	0	0	1×10^{-6}
cldwatmi_dcs	Autoconversion size threshold for ice to snow	Large-scale cloud	0.0001	0.0004	0.0005
cldwatmi_eii	Collection efficiency for the aggregation of ice	Large-scale cloud	0.001	0.1	1
cldwatmi_qcvar	Inverse relative variance of sub-grid scale cloud water	Large-scale cloud	0.5	2	5
eddydiff_a2l	Moist entrainment enhancement parameter	Turbulence	10	30	50
micropa_wsubimax	Maximum sub-grid scale vertical velocity for ice nucleation	Large-scale cloud	0.1	0.2	1
micropa_wsubmin	Minimum sub-grid scale vertical velocity for liquid nucleation	Large-scale cloud	0	0.2	1
uwschcu_criqc	Maximum updraft condensate in shallow convection	Shallow convection	0.0005	0.007	0.0015
uwschcu_kevp	Evaporative efficiency of shallow convection precipitation	Shallow convection	1×10^{-6}	2×10^{-6}	2×10^{-5}
uwschcu_rkm	Scaling factor for shallow convection entrainment rate	Shallow convection	8	14	16
uwschcu_rpen	Penetrative efficiency of shallow convection updraft	Shallow convection	1	5	10
zmconv_alfa	Initial deep convection cloud downdraft mass flux	Deep convection	0.05	0.1	0.6
zmconv_c0_lnd	Deep convection autoconversion coefficient over land	Deep convection	0.001	0.0059	0.01
zmconv_c0_ocn	Deep convection autoconversion coefficient over ocean	Deep convection	0.001	0.045	0.1
zmconv_dmpdz	Fractional mass entrainment rate for deep convection	Deep convection	0.0002	0.001	0.002
zmconv_ke	Evaporation efficiency of deep convection precipitation	Deep convection	5×10^{-7}	1×10^{-6}	1×10^{-5}
zmconv_tau	Convective adjustment time scale for deep convection	Deep convection	1800	3600	28800

1 TABLE 3. Bias and root-mean-square (RMS) errors calculated over a global domain for
2 climatological December-January-February averages between observations and various
3 model configurations. Model simulations are compared to observations of GPCP
4 precipitation, CERES EBAF shortwave cloud radiative effect (SWCRE), ocean-only
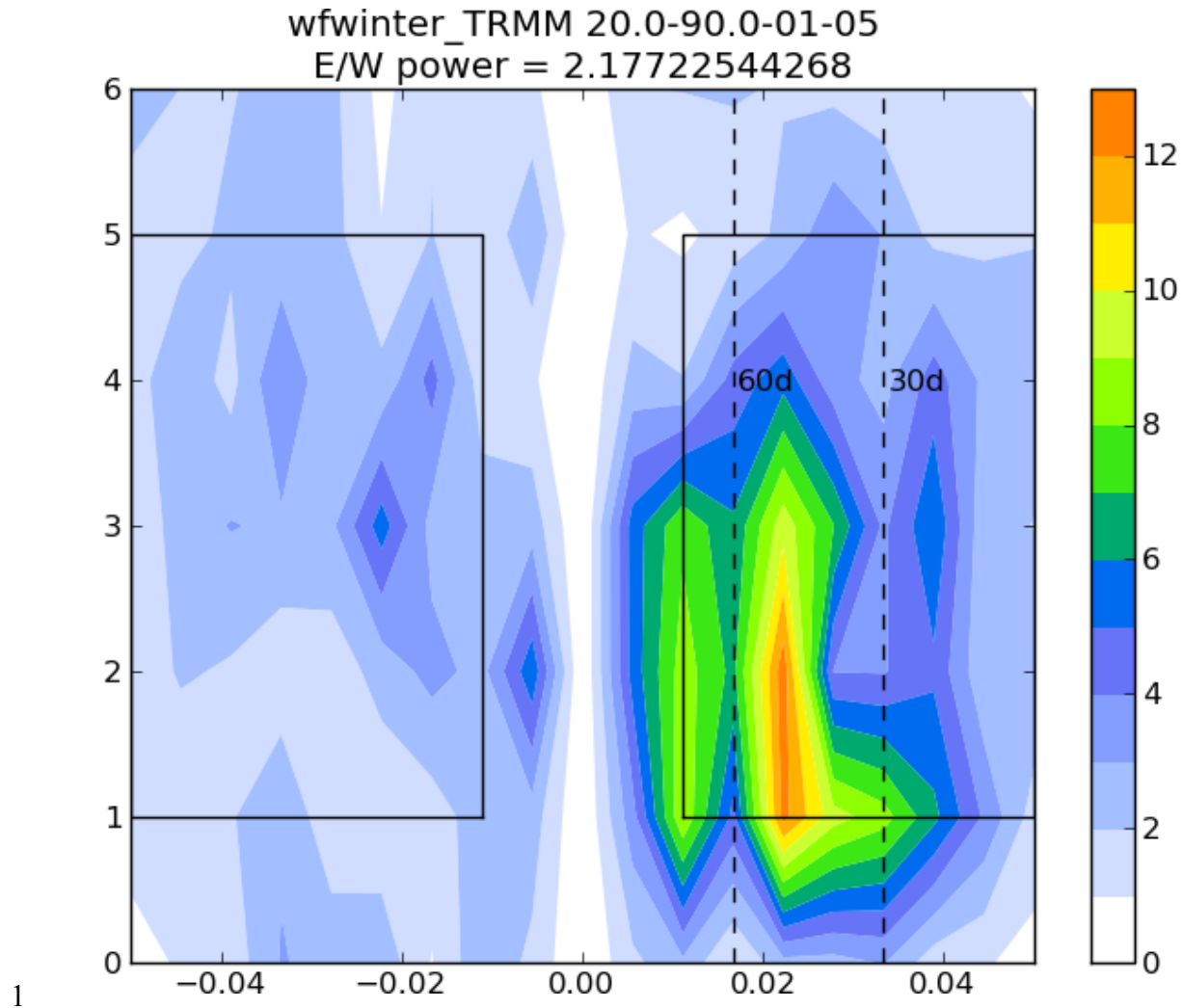5 NVAP liquid water path (LWP), and CERES EBAF OLR.

Model	GPCP (mm d^{-1})		CERES EBAF SWCRE (W m^{-2})		NVAP LWP (g m^{-2})		CERES EBAF OLR (W m^{-2})	
	Bias	RMS	Bias	RMS	Bias	RMS	Bias	RMS
Default	0.301	1.284	-2.76	21.25	-35.32	39.71	-3.95	9.967
UQ-Rec	0.179	1.314	-20.82	36.17	216.54	355.20	-7.46	13.12
PPE-Best	0.252	1.501	-27.655	41.089	188.29	303.08	-7.99	13.90
OAT38	0.225	1.232	-18.629	34.881	181.95	314.64	-7.59	13.32

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(a) TRMM Lag Correlation with IO region

(b) TRMM Lag Correlation with WP region

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FIGURE 1. Lag-longitude correlation coefficients of TRMM precipitation averaged from
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(a) EWPR and PC-IO for OAT ensemble GPCP

(b) EWPR and PC-IO for OAT ensemble TRMM

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FIGURE 3. Joint histogram across the ensemble of East-West Power Ratio (*wePwrRatio*)
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9 including CAM5's default to lead to simulations which more closely match the observed
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(a) Obs

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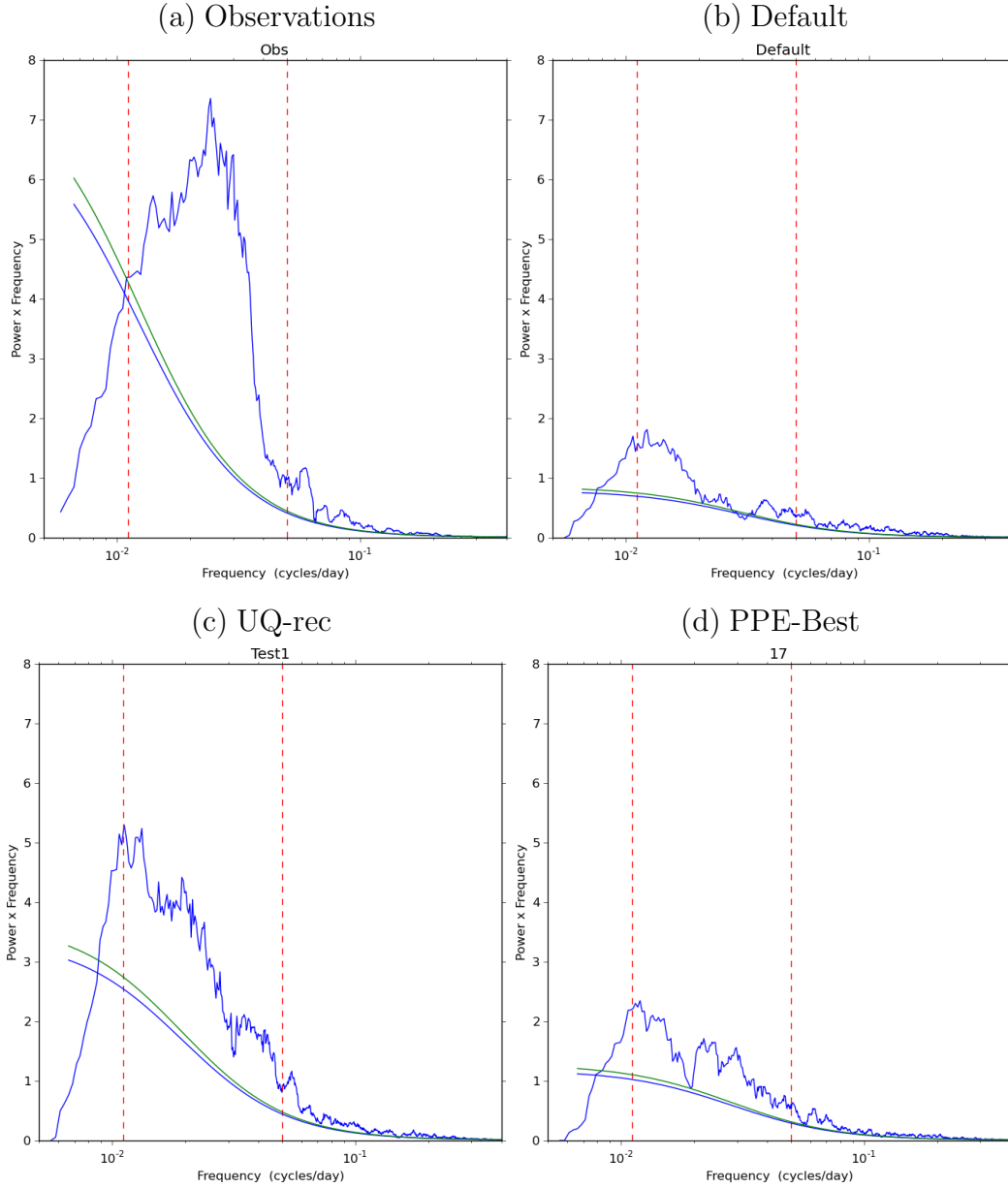
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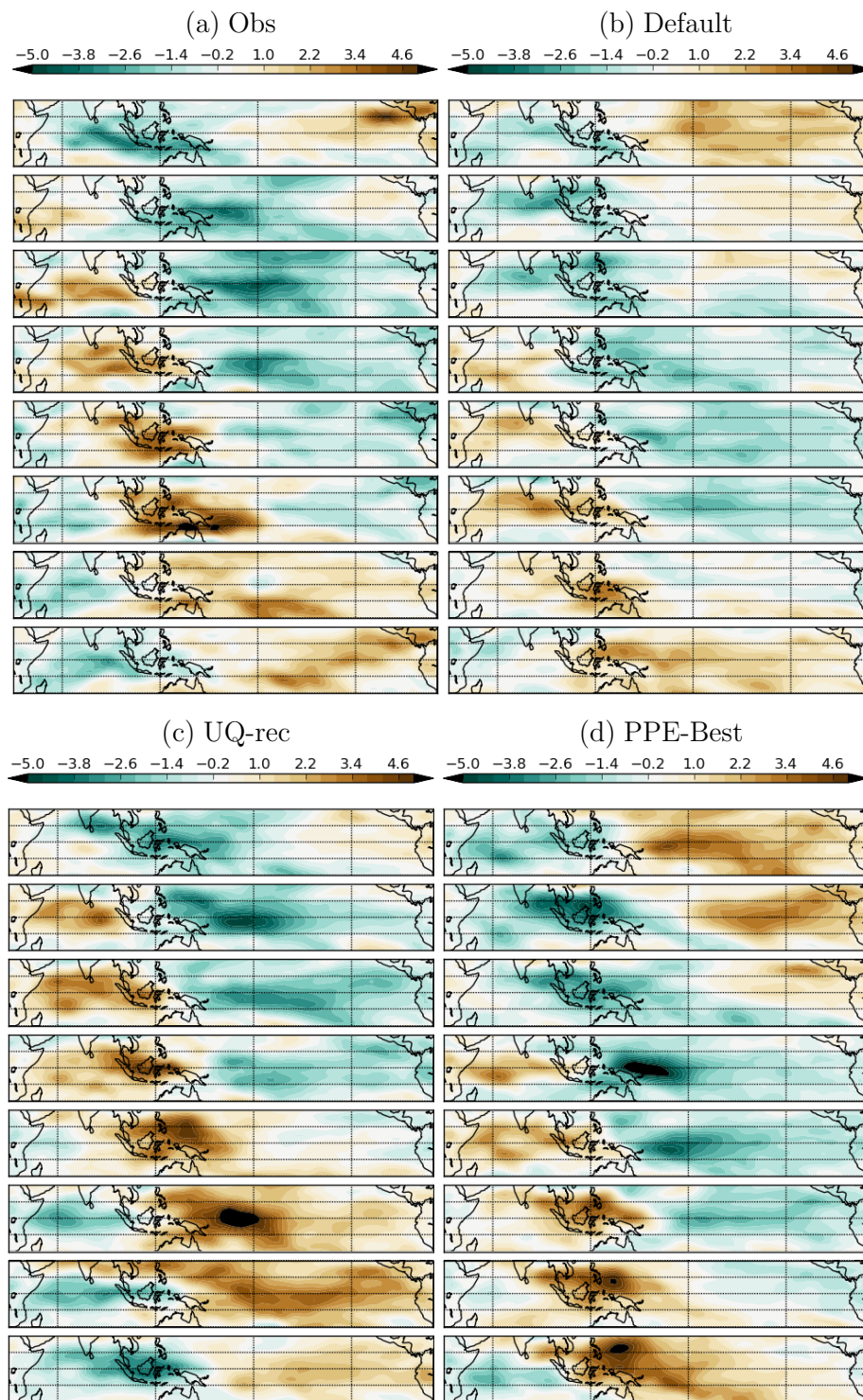
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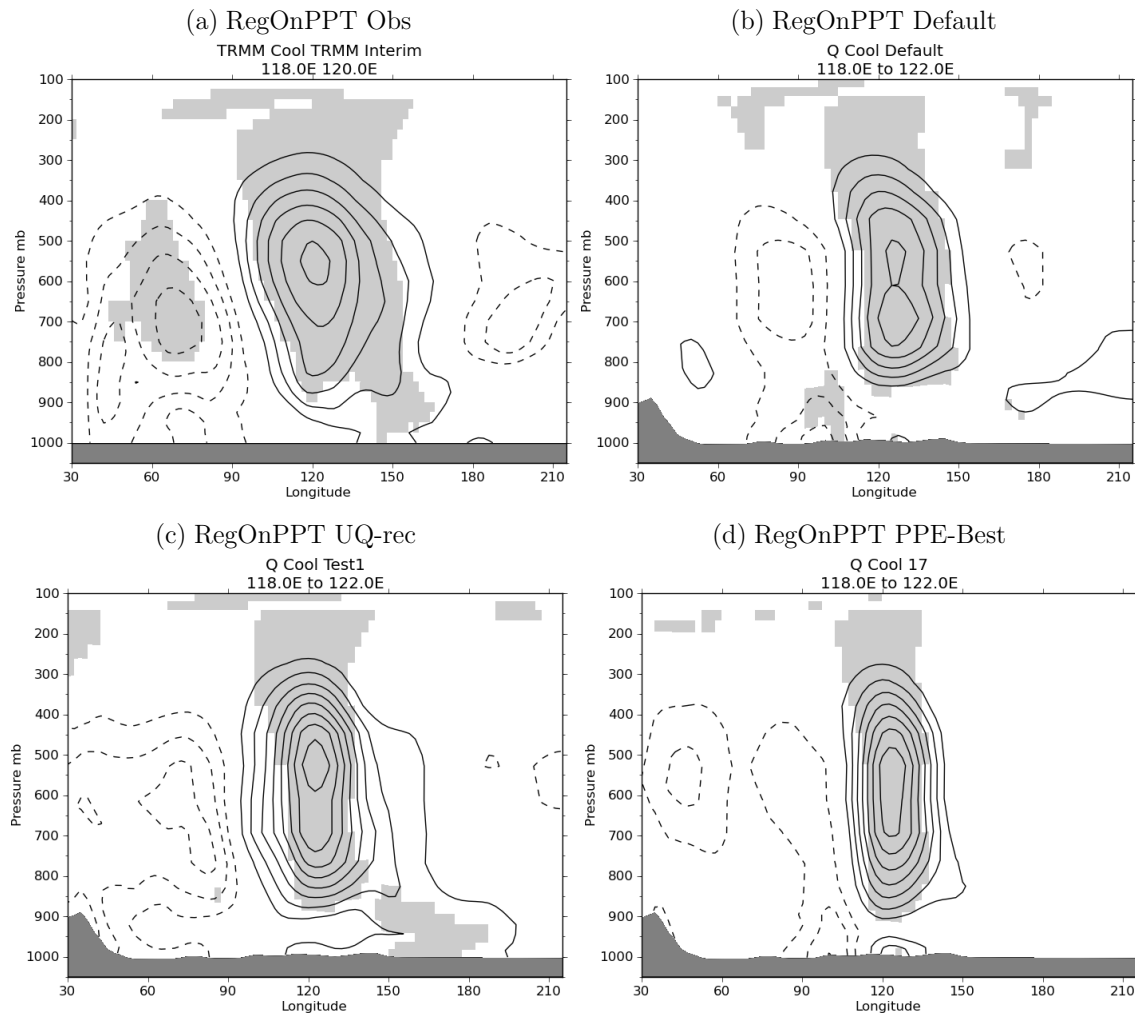(a) Obs

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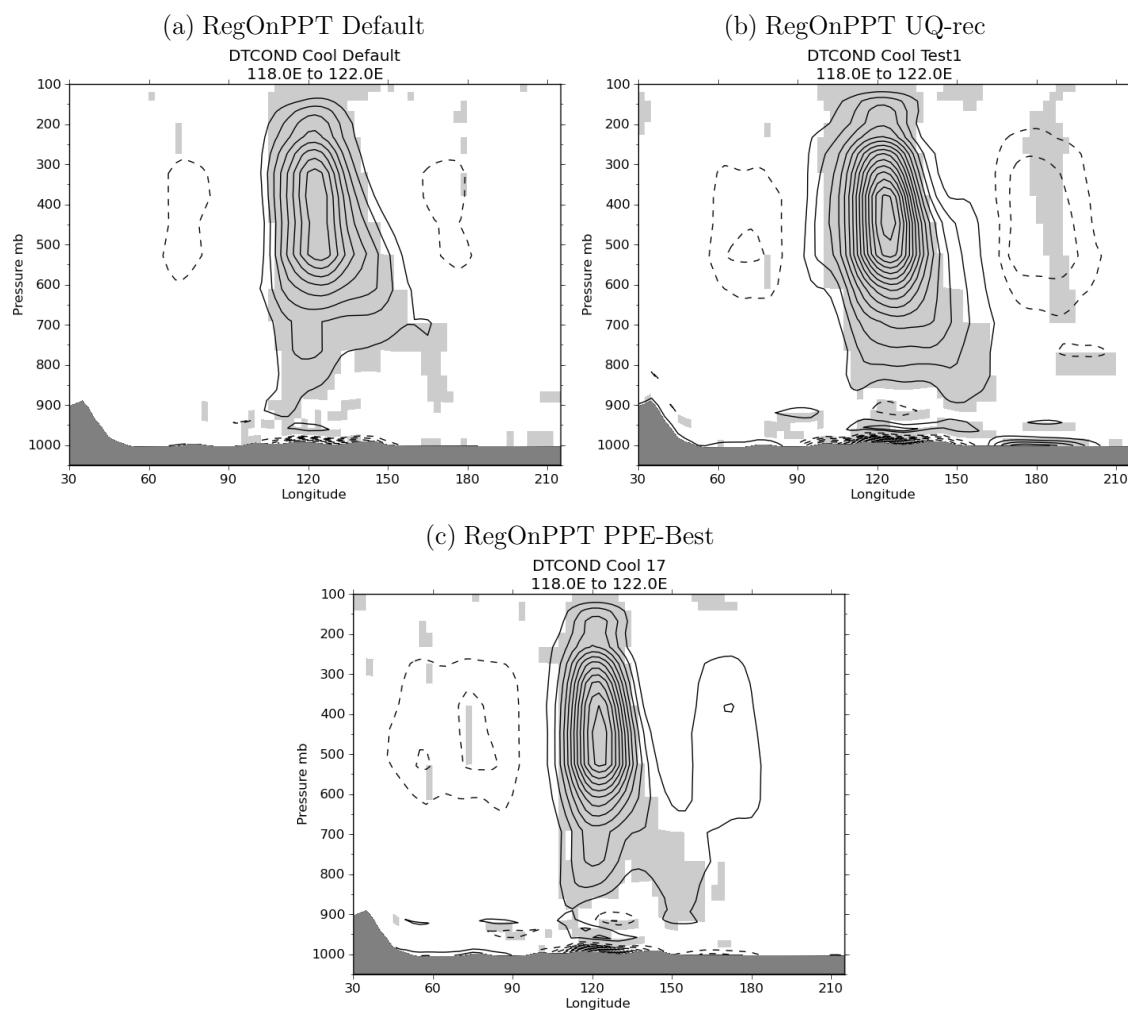
(a) Obs (b) Default (c) UQ-rec (d) PPE-Best

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(a) RegOnPPT Obs

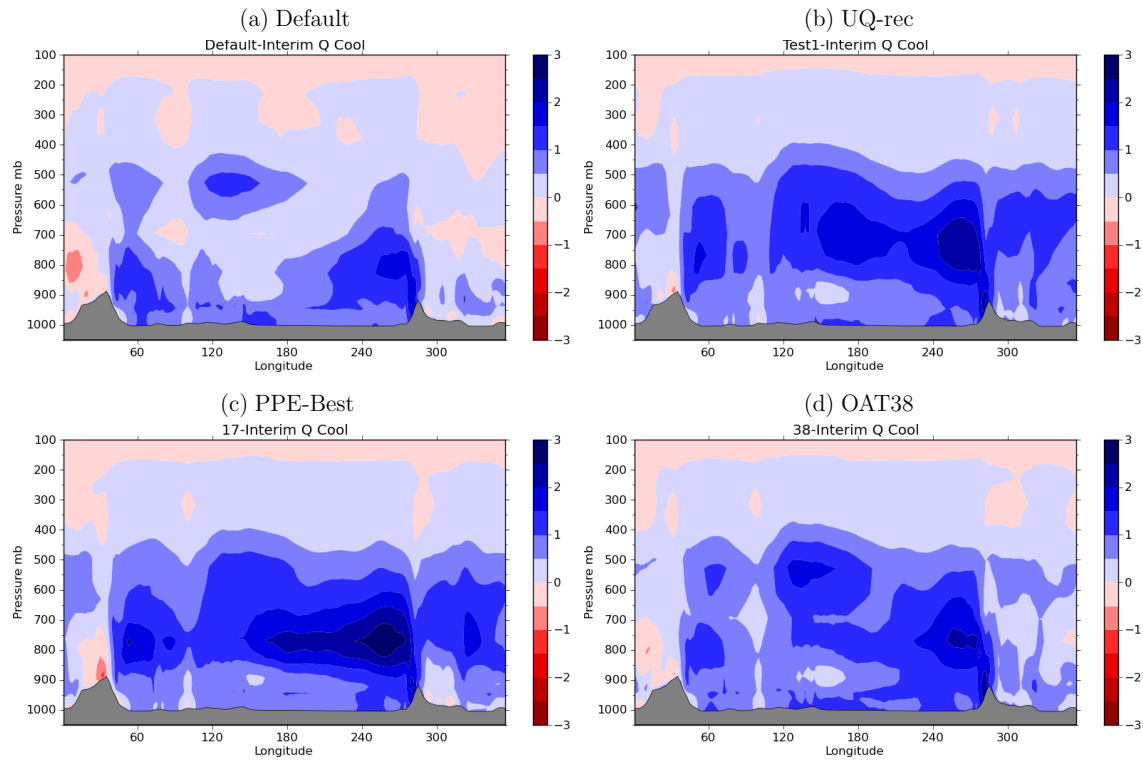(b) RegOnPPT Default

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